

A Framework for Self-Regulated Learning Utilizing AI to Support Students with Learning Disabilities in Inclusive Classrooms

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ABSTRACT:

Inclusive educational systems commonly encompass students with learning disabilities, including dyslexia, dysgraphia, dyscalculia, and executive-function challenges, characterized by enduring struggles in attention regulation, working memory, planning, and autonomous task completion. These impediments contribute to educational inequality and diminished levels of learning engagement. Simultaneously, educators encounter notable obstacles in delivering consistent tailored support while managing instruction for the entire class, constraining their capacity to effectively cater to a diverse student body.

Despite the objectives of inclusive educational directives to enhance educational access, school involvement, and equal opportunities, implementation shortcomings persist. Learners with special education needs frequently necessitate continual metacognitive assistance, a challenging provision within extensive, varied classroom settings. Although Self-Regulated Learning (SRL) is pivotal for academic triumph, numerous students lack the requisite executive functioning proficiencies to

autonomously apply SRL techniques. While Universal Design for Learning (UDL) bolsters instructional adaptability, it falls short in offering uninterrupted personalized support

This article advocates an Artificial Intelligence (AI)-backed SRL framework that merges AI technologies such as intelligent tutoring systems, learning analytics, and generative AI to bolster planning, performance, and introspection. The framework amplifies goal establishment, task dissection, monitoring, feedback provision, and directed reflection, thereby enriching learning opportunities and inclusive pedagogical approaches.

Educators retain a central role as educational facilitators who interpret AI-derived insights, tweak scaffolding, and gradually nurture learner autonomy. The framework aligns with Sustainable Development Goal 4 (Quality Education) by advancing inclusive and equitable education and Goal 10 (Reduced Inequalities) by heightening accessibility and involvement for students with specialized educational requirements.

Keywords: Artificial Intelligence in Education (AIED); Self-Regulated Learning (SRL); Universal Design for Learning (UDL); Special Education Needs; Inclusive Education System

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1. Introduction

Inclusive education has become a global priority supported by international commitments such as the Salamanca Statement by UNESCO and the United Nations Sustainable Development Goal 4 (Quality Education), both of which advocate equitable participation and achievement for learners with disabilities within a robust inclusive education system. (United Nations, 2023; United Nations Human Rights Council, 2024). Despite these commitments, learners with special education needs, including dyslexia—including dyslexia, dysgraphia, dyscalculia, and executive-function challenges—continue to encounter barriers that affect attention regulation, working memory, planning, and metacognitive monitoring. These cognitive characteristics directly influence their ability to engage in independent learning processes, even within a well-designed educational environment (Wider et al., 2026).

Self-Regulated Learning (SRL) has been widely recognized as a key predictor of academic

success. The socio-cognitive models advanced by Barry Zimmerman conceptualize SRL as a cyclical process involving goal setting, strategic planning, performance monitoring, and reflective evaluation. However, for learner with special education needs, the executive-function skills required to enact SRL are often the very areas of difficulty. Consequently, expectations for independent self-regulation without sustained scaffolding may unintentionally reproduce education inequities within inclusive education system. Although the principles of CAST Universal Design for Learning (UDL) advocate reducing barriers through multiple means of engagement, representation, and expression, UDL does not fully operationalize how continuous, individualized metacognitive support can be provided in real time for learners diverse learning opportunities for those who struggle with regulation (Lim et al., 2024).

Recent advances in Artificial Intelligence in education offer capabilities such as adaptive feedback, learning analytics, and personalized task pathways. These affordances create

possibilities for AI systems to function as cognitive partners that prompt goal setting, monitor progress, and support reflection—core processes of SRL (Mejeh et al., 2024). However, most AI applications in special education needs focus on basic accessibility tools rather than structured metacognitive scaffolding. Moreover, the literature lacks a coherent conceptual integration of AI capabilities with established SRL theory specifically for an inclusive education system (Mejeh et al., 2024; Chiu, 2024).

This gap reveals a critical problem: while inclusive pedagogy, SRL theory, and AI technologies have each developed substantially, they remain insufficiently connected in ways that directly address the educational inequality faced by these learners. Existing instructional approaches rely heavily on teacher-mediated scaffolding, which may be limited by time and resources. There is, therefore, a need for a theoretically grounded model that serves as an educational reform, illustrating how AI can provide structured, adaptive scaffolding for self-regulation within a modern educational environment (United Nations, 2023; Chiu, 2024).

Addressing this need, the present paper aims to

- (1) synthesize theoretical foundations from SRL, inclusive education, and AI in education
- (2) develop a conceptual AI-supported SRL framework tailored to students with learning disabilities
- (3) demonstrate how AI-driven scaffolding can enhance goal setting, monitoring, feedback, and reflection processes
- (4) outline implications for classroom implementation and future empirical research.

Research Questions

- How can AI technologies be aligned with SRL models to support students with learning disabilities?
- What components are essential in an AI-supported SRL framework for inclusive classrooms?

- How can such a framework embody UDL principles?
- What implications does this framework hold for research and practice?

By integrating these perspectives, this study advances the discussion from whether inclusion is achievable to how inclusive classrooms can be intelligently designed to strengthen the self-regulatory capacities of students with learning disabilities through AI-supported pedagogical scaffolding.

2. Literature Review

Self-regulated learning (SRL) stands as a fundamental aspect of modern educational reform, empowering students to actively oversee their educational progress through activities such as goal establishment and reflective assessment (Yeboah & Oloto, 2024). The amalgamation of SRL with artificial intelligence and inclusive education addresses a significant void in the inclusive education system, where conventional standardized approaches often fail to reduce educational inequality (Ahmed et al., 2025).

Students with special education needs encounter substantial obstacles to educational access and equal opportunities in traditional settings (Wang et al., 2025). Nevertheless, emerging indications propose that personalized learning systems can enrich the educational environment and cultivate diverse learning opportunities when crafted with inclusivity at the forefront (Lim et al., 2024; Wang et al., 2025).

SRL finds its roots in social-cognitive theory and is depicted as a cyclical progression encompassing phases of anticipation, execution, and contemplation (Zimmerman, 2000). This standpoint holds particular relevance for learners with special education needs, emphasizing the criticality of explicit instruction on strategies and scaffolded aid to ensure equal opportunities for academic success (Panadero, 2017; Anyichie, 2025).

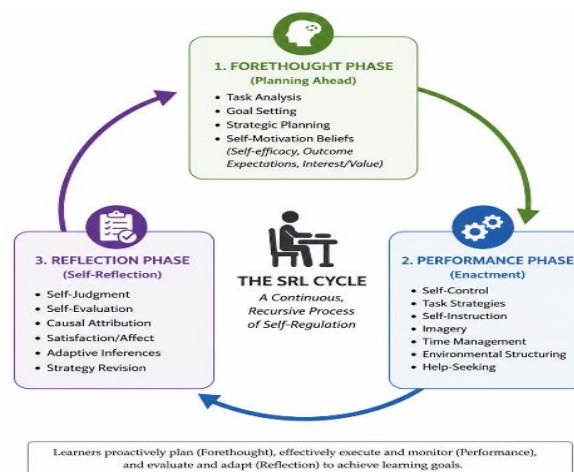


Figure 1: Zimmerman's Standard Self-Regulated Learning Cycle.

The graphical representation in Figure 2 illustrates the intricate interplay among the elements in the suggested framework. The structure embodies an integrated stratified environment aimed at transitioning from fixed supportive modifications to adaptive, metacognitive support.

The forethought phase involves goal setting and planning, where students develop specific, measurable objectives aligned with their learning needs (Zimmerman, 2000). The performance phase requires continuous self-monitoring and strategic execution, while the reflection phase encompasses self-evaluation and adaptive strategy adjustment. For learner with special education needs, explicit instruction in each phase—coupled with technological support—significantly enhances their capacity for autonomous learning (Chang et al., 2023; Achuthan, 2025). Self-Determination Theory (SDT) identifies autonomy, competence, and relatedness as fundamental psychological needs essential for sustained motivation and engagement (Deci & Ryan, 2000). In inclusive education system, AI-supported SRL frameworks must address these needs by providing flexible learning options (autonomy), scaffolded challenges that build confidence (competence), and collaborative learning opportunities (relatedness) (Ryan & Deci, 2017). Learners with special education needs often experience compromised self-efficacy due to

repeated academic failures; therefore, AI systems must be designed to provide immediate, constructive feedback that gradually builds confidence and motivation (Akhter & Shaheen, 2026).

Metacognition—defined as awareness and regulation of one's own thinking processes—serves as a central mechanism of self-regulated learning (Flavell, 1979; Schraw & Moshman, 1995). Students with special education needs often demonstrate weaker metacognitive control, particularly in planning, monitoring, and evaluation processes, which limits their ability to independently regulate learning (Fletcher et al., 2019; Bouargane et al., 2024). Recent research indicates that AI-supported educational environments can address these challenges by providing adaptive prompts, visual progress tracking, and scaffolded reflection activities that help externalize metacognitive processes during learning (Kasneji et al., 2023). Empirical findings further show that explicit instruction in metacognitive strategies, when combined with technology-enhanced feedback systems, significantly improves learners' strategy use and academic performance thereby advancing equal opportunities across diverse populations (Jin et al., 2023; Ouyang, 2025).

Universal Design for Learning (UDL) provides a proactive instructional framework aimed at educational access and reducing educational inequality through multiple means of

engagement, representation, and action/expression (CAST, 2018; Meyer et al., 2014). Rather than retrofitting accommodations, UDL anticipates learner variability and embeds flexibility into curriculum design from the outset, making it particularly effective in inclusive education system (CAST, 2018; Capp, 2017; Melo-López et al., 2025). In technology-enhanced educational environment, UDL operates synergistically with AI-supported self-regulated learning by ensuring that digital tools are accessible, adaptable, and responsive to diverse learning opportunities while simultaneously strengthening students' capacity for autonomous learning regulation (Meyer et al., 2014; Banihashem et al., 2025).

The three Universal Design for Learning (UDL) principles directly support SDG 4 (Quality Education) by promoting inclusive, equitable, and accessible learning opportunities. Multiple Means of Representation ensures content is delivered in diverse formats (text, visual, and auditory), accommodating varied cognitive and sensory needs and improving educational access for all learners (CAST, 2018; Manly, 2024). Multiple Means of Engagement enhances learner motivation through autonomy, relevance, and scaffolded challenge, which contributes to sustained participation and reduced disengagement in diverse educational environment (CAST, 2018; Jin et al., 2023). Multiple Means of Action and Expression further strengthens educational equity by enabling learners to demonstrate understanding through multiple modalities, reducing structural bias in traditional assessment systems (CAST, 2018; Capp, 2017; Ahmed et al., 2025). Collectively, these principles operationalize SDG 4 by ensuring inclusive and equitable quality education for learners with special education needs.

In relation to SDG 10 (Reduced Inequalities), co-teaching models—where general and special educators collaboratively design instruction—play a critical role in educational inequality for learners with special education needs (Rytivaara et al., 2024; Wider et al., 2026). When integrated with AI-supported self-regulated learning (SRL) systems, this model strengthens equity by

combining human-centred pedagogical support with adaptive technological scaffolding. Teachers provide relational, culturally responsive instruction, while AI systems offer individualized feedback, real-time analytics, and adaptive learning pathways that respond to learner variability (Kasneci et al., 2023; Zawacki-Richter et al., 2019). This dual-layer support system reduces learning gaps by ensuring that students who are traditionally underserved receive continuous, personalized learning assistance (Ahmed et al., 2025; Holmes et al., 2021).

Differentiated instruction further reinforces both SDG 4 and SDG 10 by tailoring learning experiences to student readiness, interests, and learning profiles (Tomlinson, 2014). When combined with AI-driven adaptive learning systems, differentiation becomes dynamic and data-informed, allowing real-time instructional adjustments within the educational environment that prevent learners from being left behind (Pagliara et al., 2024; Barrera Castro et al., 2026). For students with special education needs, such systems provide targeted scaffolding that enhances engagement and educational access, thereby reducing structural educational inequities and increasing learning opportunities (Jin et al., 2023; Menikdiwela et al., 2026).

Intelligent Tutoring Systems (ITS) and adaptive learning platforms form the technological backbone for achieving SDG 4 through personalized and inclusive learning pathways (Kasneci et al., 2023; Zaraii Zavaraki, 2024). These systems leverage machine learning to model learner cognition, detect misconceptions, and generate individualized instructional sequences (Chang et al., 2023). For learners with special education needs, ITS enhance equity by offering adaptive pacing, multimodal explanations, and immediate feedback that compensate for learning barriers equal opportunities for education success (Kasneci et al., 2023; Menikdiwela et al., 2026). The integration of generative AI systems further advances Quality Education (SDG4) by supporting metacognitive development and personalized learning at scale (Kasneci et al., 2023; Jin et al., 2023). These tools facilitate

inclusive education by generating tailored explanations, scaffolding reflection, and adapting communication styles to individual learner needs (Kasneci et al., 2023; Li et al., 2025). From an SDG 10 perspective, generative AI reduces educational inequities by providing continuous learning support to students who may lack access to individualized human tutoring, particularly learners with special education needs (Ahmed et al., 2025). However, equitable implementation requires careful pedagogical design. Without structured integration, generative AI risks reinforcing inequities through superficial “answer-harvesting” behaviors that limit deep learning (Menikdiwela et al., 2026). Therefore, AI must be positioned as a reflective cognitive partner that enhances rather than replaces learner effort, ensuring alignment with both SDG 4’s emphasis on quality learning and SDG 10’s focus on reducing educational inequality (Kasneci et al., 2023; Jin et al., 2023). Learning analytics systems further support both SDG 4 and SDG 10 by making learning processes visible and actionable within the educational environment (Siemens & Long, 2011; Ferguson, 2012; Ahmed et al., 2025). Dashboards enhance self-regulated learning by enabling goal tracking, reflection, and adaptive strategy use, thereby strengthening learner autonomy (Zhang, 2026). Importantly, such transparency is particularly beneficial for students with special education needs, as it externalizes progress and reduces hidden learning barriers

(Winne & Hadwin, 1998; Menikdiwela et al., 2026).

Finally, machine learning-driven predictive analytics contribute to equal opportunities by identifying at-risk learners early and enabling proactive intervention (Ahmed et al., 2025). Early warning systems improve retention and engagement by detecting patterns of difficulty before failure occurs, thereby directly supporting SDG 10 through the prevention of widening achievement gaps (Siemens & Long, 2011; Ikram et al., 2026). In inclusive education contexts, these systems ensure that students with special education needs receive timely, targeted support rather than reactive remediation, reinforcing both educational access and educational quality (Ikram et al., 2026).

Development of the Conceptual Framework

Based on the synthesis of literature on Self-Regulated Learning (SRL), Universal Design for Learning (UDL), and Artificial Intelligence (AI) in education, this section presents the development of an integrated conceptual framework for Quality Education (SDG 4) supporting students with special education needs in a contemporary, technology-infused educational environment (Zimmerman, 2000; CAST, 2018; Wang et al., 2025).

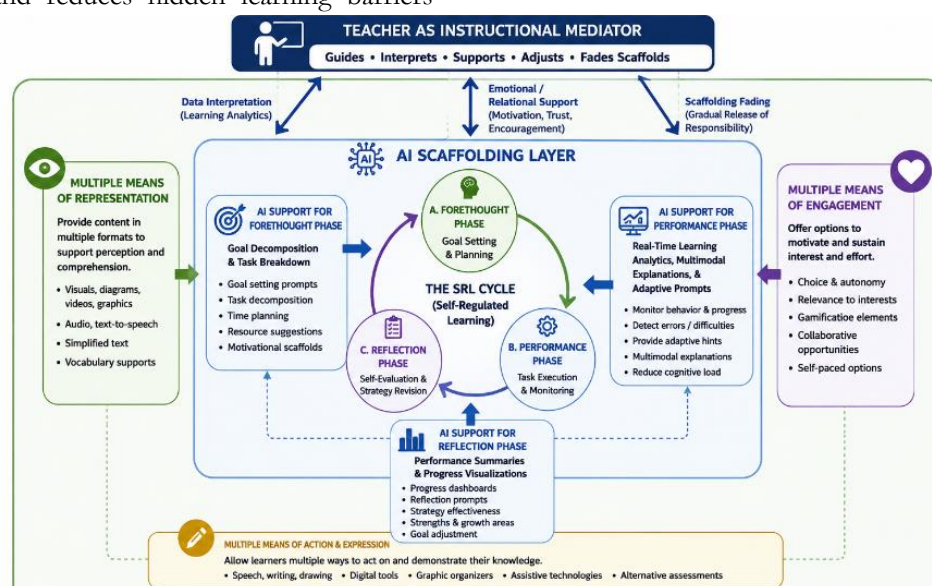


Figure 2: Matrix for Inclusive Classrooms Incorporating AI-Supported SRL Hybrid Framework.

The diagram depicted in Figure 2 demonstrates the operational design of a comprehensive system in which the three-stage Self-Regulated Learning (SRL) process is intricately embedded within the foundational tenets of Universal Design for Learning (UDL). In contrast to a solitary automated mechanism, this system introduces a stratified structure in which artificial intelligence functions as a flexible cognitive support mechanism under the ongoing assessment, interpersonal backing, and educational guidance of the teacher in the classroom.

The forethought phase is operationalized as a digitally scaffolded planning environment in which AI systems support learners in translating abstract learning goals into structured, actionable steps (Zimmerman, 2000; Chang et al., 2023). Rather than requiring learners with special education needs to independently generate and organize complex learning plans, AI tools provide guided goal decomposition by suggesting incremental sub-goals aligned with curriculum standards and individual learner profiles. These systems also incorporate motivational scaffolds such as adaptive encouragement messages, predictive success indicators, and personalized learning pathways that enhance expectancy-value beliefs (Eccles & Wigfield, 2020; Chang et al., 2023). This is particularly important because students with learning disabilities often experience reduced academic self-efficacy due to repeated experiences of failure, which can negatively impact goal initiation and persistence (Zimmerman, 2000; Chang et al., 2023).

During the performance phase, the framework emphasizes continuous, real-time interaction between learners and AI-driven adaptive systems (Zimmerman, 2000; Afzaal & Nouri, 2024). These systems function as cognitive monitors that track learner engagement, detect cognitive overload, and identify performance gaps through learning analytics and behavioural data patterns (Siemens & Long, 2011; Ferguson, 2012; Palanci, 2024).

When difficulties are detected, the system responds with timely interventions such as hint generation, step-by-step guidance, or multimodal

explanations. This adaptive responsiveness reduces cognitive overload and supports sustained task engagement, particularly to ensure educational access for learners with special education needs (Chang et al., 2023). In addition, AI-generated prompts encourage learners to engage in self-monitoring behaviours, such as checking progress against goals, evaluating strategy effectiveness, and adjusting approaches when necessary (Sweller, 2011; Kasneci et al., 2023). Over time, repeated exposure to these prompts supports the internalization of metacognitive monitoring skills.

The reflection phase is designed as a structured metacognitive evaluation space supported by AI-generated feedback summaries and visualization tools (Zimmerman, 2000; Panadero, 2017; Chang et al., 2023). Learners are presented with explicit depictions of their performance patterns, encompassing strengths, mistakes, and advancement trajectories (Siemens & Long, 2011; Afzaal & Nouri, 2024). These representations are deliberately crafted in user-friendly formats, such as interactive dashboards or simplified visual progress diagrams, to ensure equal opportunities so that learners with special education needs can autonomously analyse their educational data (Menikdiwela et al., 2026). Through the externalization of these internal procedures via visual tools, the framework diminishes the metacognitive burden necessary for self-assessment, allowing students to pinpoint effective tactics and areas necessitating enhancement without being inundated by abstract data (Pagliara et al., 2024).

In addition, reflective scaffolds guide learners through structured questions that prompt deeper cognitive processing, such as evaluating which strategies were effective, identifying challenges encountered, and considering alternative approaches for future tasks (Panadero, 2017; Chang et al., 2023). This structured reflection is essential for developing accurate self-assessment skills.

Across all phases, AI operates as an adaptive scaffolding layer; however, its effectiveness depends on integration with pedagogical design

principles grounded in Universal Design for Learning (UDL) (CAST, 2018; Kasneci et al., 2023). The framework ensures that instructional content is delivered through multiple means of representation, engagement, and expression, thereby expanding educational access and reducing educational inequality (CAST, 2018; UNESCO, 2025). This integration allows AI systems not only to personalize content delivery but also to align with inclusive instructional design principles that accommodate learner variability.

Importantly, the framework also emphasizes teacher mediation as a critical regulatory layer (Vygotsky, 1978; UNESCO, 2025). Teachers interpret AI-generated insights, contextualize feedback, and provide relational and emotional support that cannot be replicated by automated systems. This teacher–AI partnership ensures that technology enhances rather than replaces human instructional judgment.

Overall, the integration of SRL theory, AI-driven adaptive systems, and UDL principles forms a cohesive conceptual structure that aims to enhance learner autonomy within the inclusive education system while maintaining necessary scaffolding for learners with special education needs (Zimmerman, 2000; CAST, 2018; Wang et al., 2025).

SRL Cycle as the Core Structure

The forethought phase involves goal setting, strategic planning, and motivational beliefs. Within the proposed framework, AI systems support this phase by assisting students in setting personalized and achievable learning goals, breaking complex tasks into manageable steps, and providing prompts that guide planning (Zimmerman, 2000; Chang et al., 2023). This aligns with research showing that structured goal-setting interventions significantly improve academic engagement and task initiation for learners with special education needs (Chang et al., 2023). Beyond basic goal formulation, AI systems further enhance this phase by analysing prior learning behaviours to recommend appropriately challenging goals aligned with the learner's zone of proximal development

(Vygotsky, 1978; Melo-López et al., 2025). This adaptive calibration helps prevent both cognitive overload and under-stimulation, which are common barriers to educational access for learners with special education needs. In addition, motivational scaffolds such as progress visualization, achievement forecasting, and personalized encouragement messages strengthen learners' expectancy of success and task value, thereby supporting sustained engagement within the inclusive education system. (Eccles & Wigfield, 2020; Chang et al., 2023).

The performance phase focuses on task execution, self-monitoring, and strategy use (Zimmerman, 2000; Winne & Hadwin, 1998). In this phase, AI-supported tools provide real-time feedback, adaptive prompts, and learning analytics dashboards that help students monitor progress and adjust strategies (Paulsen & Lindsay, 2024). These supports are particularly critical to ensure equal opportunities for learners with special education needs, who often struggle with sustained attention and working memory limitations (Ahmed et al., 2025). The framework further integrates adaptive metacognitive prompting, where AI systems actively guide learners through strategic thinking by asking reflective questions such as "What strategy are you using?" or "Why do you think this answer is incorrect?" (Winne & Hadwin, 1998; Chang et al., 2023). These prompts externalize internal cognitive processes and promote self-explanation, which is known to enhance deep learning and knowledge transfer (Melo-López et al., 2025). In addition, multimodal feedback—such as visual indicators, auditory cues, and step-by-step scaffolds—ensures accessibility for learners with diverse cognitive and sensory needs (CAST, 2018; Melo-López et al., 2025). This reduces cognitive load and supports sustained engagement within the educational environment, particularly for learners with special education needs. Another essential component of this phase is error-based learning support, where AI systems reframe mistakes as learning opportunities rather than failures (Kasneci et al., 2023; Aliu, 2024). When persistent errors occur,

the system provides scaffolded hints, alternative explanations, or simplified task versions. This adaptive error management strategy helps maintain motivation and promotes persistence, which is often a challenge for students with special education needs.

The reflection phase involves self-evaluation, attribution, and adaptive strategy revision (Zimmerman, 2000; Panadero, 2017). Within the educational environment, AI systems contribute by generating performance summaries, highlighting progress trends, and prompting

reflective questions that guide learners to evaluate their learning strategies (Menikdiwela et al., 2026). Beyond performance reporting, AI tools support deep metacognitive reflection by identifying patterns across tasks and subjects, enabling learners to extend their learning opportunities by determine which strategies are most effective in different contexts (Kasneci et al., 2023). Comparative analytics further enhance this process by allowing students to track progress over time, fostering a sense of improvement and self-awareness (Melo-López et al., 2025).

Table 1: Mapping of SRL Phases to AI Functions

SRL Phase	Learner Need	AI Function	Example Tools/Outputs	Expected Outcome
Forethought	Goal setting, planning, motivation	Decomposition of objectives, feedback on predictive achievements, dynamic cues.	Smart goal planner, AI task breakdown	Improved goal clarity and motivation
Performance	Monitoring, attention control, strategy use	Immediate data analysis, flexible response, varied explanations.	Dashboards, tutoring systems	Improved engagement and task persistence
Reflection	Self-evaluation, strategy adjustment	Summative assessments, introspective cues, educational data analyses	Progress visualization tools	Enhanced metacognitive awareness

Moreover, AI systems support attributional awareness by helping learners distinguish between effort, strategy use, and external factors influencing performance (Graham & Taylor, 2020; Chang et al., 2023). This is particularly important in preventing maladaptive attribution patterns, such as attributing failure solely to ability, which is common among learners with special education needs (Zimmerman, 2000). By encouraging constructive attributional thinking, the framework promotes a growth-oriented mindset and strengthens long-term academic resilience (Kasneci et al., 2023).

Collectively, these enhancements ensure that each phase of the SRL cycle is not only supported but dynamically enriched through AI-driven scaffolding. The result is a responsive and adaptive educational environment that integrates cognitive, motivational, and metacognitive support, enabling students with special education needs to progressively develop greater autonomy within inclusive educational system to ensure equal opportunities for educational success (Zimmerman, 2000; Kasneci et al., 2023).

Integration of Artificial Intelligence as a Scaffolding Layer

Within the framework, Artificial Intelligence functions as a dynamic scaffolding layer that operates across all SRL phases (Kasneci et al., 2023). AI tools such as intelligent tutoring systems, learning analytics platforms, and generative AI applications provide adaptive support based on performance data within educational environment (Chang et al., 2023). These systems identify learning patterns, detect difficulties early, and deliver personalized interventions that align with exact special education needs (UNESCO, 2025).

Importantly, AI is not positioned as a replacement for human instruction but as an augmentation tool that enhances the teacher's capacity to provide timely and individualized support (Holmes et al., 2021). This aligns with evidence suggesting that teacher-mediated AI integration is more effective than fully autonomous AI systems, particularly in special education contexts (Wang et al., 2025).

Universal Design for Learning as the Structural Foundation

Within the proposed framework, Artificial Intelligence functions as a dynamic scaffolding layer that operates across all phases of the Self-Regulated Learning (SRL) cycle (Zimmerman, 2000; Chen et al., 2025). AI-based tools such as intelligent tutoring systems, learning analytics platforms, and generative AI applications provide adaptive and context-sensitive support grounded in real-time learner performance data (Chang et al., 2023). These systems continuously analyse patterns of learner interaction, detect emerging difficulties, and deliver personalized interventions that align with individual cognitive, motivational, and academic needs (Ahmed et al., 2025). For students with learning disabilities, this adaptive responsiveness is particularly significant because it helps to reduce cognitive overload, provides timely clarification of misconceptions, and supports sustained engagement in tasks that might otherwise lead to frustration or disengagement (Ahmed et al., 2025). Rather than offering static instructional content, AI systems

dynamically adjust the learning environment by modifying task difficulty, providing scaffolded hints, and offering multimodal explanations that match learner preferences and processing strengths (UNESCO, 2025; Boulhrir et al., 2025).

Importantly, AI is not conceptualized as a replacement for human instruction but rather as an augmentation mechanism that enhances the teacher's ability to provide timely, targeted, and individualized support (Holmes et al., 2021; UNESCO, 2025). In this framework, the teacher remains central to the instructional process, while AI acts as collaborative orchestrator that extends the teacher's capacity to monitor student progress and respond to diverse learning needs within inclusive classrooms (Holmes et al., 2021; UNESCO, 2025). This aligns with empirical evidence suggesting that teacher-mediated AI integration yields more effective learning outcomes compared to fully autonomous AI systems, particularly in special education contexts where relational empathy, emotional understanding, and pedagogical judgment are essential (Kasneci et al., 2023; Wang et al., 2025). The combination of human expertise and machine intelligence therefore creates a hybrid instructional environment in which each complements the limitations of the other: AI provides precision, scalability, and real-time adaptation, while teachers provide empathy, contextual interpretation, and ethical decision-making (Holmes et al., 2021; Kasneci et al., 2023).

Parallel to the AI scaffolding layer, the framework is grounded in the principles of Universal Design for Learning (UDL), which serves as the structural foundation ensuring that instruction is inherently inclusive and responsive to learner variability (CAST, 2018; UNESCO, 2025; Kasneci et al., 2023). UDL emphasizes the proactive design of learning environments that accommodate diverse learner needs from the outset, rather than retrofitting accommodations after barriers emerge (Capp, 2017; Meyer et al., 2014). The framework incorporates the three core UDL principles: multiple means of representation, multiple means of engagement, and multiple means of action and expression (CAST, 2018). Multiple means of representation

ensure that instructional content is delivered through varied formats, including textual, visual, auditory, and interactive multimodal resources, thereby supporting learners with different perceptual and cognitive preferences (Evmenova et al., 2024). Multiple means of engagement enhance learner motivation by offering choice, relevance, autonomy, and appropriately scaffolded challenge, which is particularly

important for sustaining attention and persistence among students with learning disabilities (Manly, 2024). Multiple means of action and expression allow learners to demonstrate understanding through diverse modalities such as speech, writing, visual representation, or digital interaction, thereby reducing the constraints imposed by traditional assessment methods (Evmenova et al., 2024).

Table 2: Alignment of UDL Principles with AI-Supported Learning

UDL Principle	Description	AI Support Strategy	Example Application
Multiple Means of Representation	Different ways of presenting information	Text-to-speech, visual aids, multimodal content	AI converts text into diagrams/audio
Multiple Means of Engagement	Motivation and participation support	Adaptive challenge level, gamification, personalized encouragement	AI adjusts task difficulty automatically
Multiple Means of Action & Expression	Different ways to show learning	Speech-to-text, creative outputs, adaptive assessments	Students submit audio/video answers

Together, these UDL principles ensure that AI-supported SRL interventions are not only technologically advanced but also pedagogically inclusive and accessible (Manly, 2024). By integrating UDL with AI-driven adaptive systems, the framework creates a learning environment that is flexible, responsive, and capable of accommodating a wide range of cognitive and learning differences (Evmenova et al., 2024). This integration ensures that inclusivity is embedded at both the design and implementation levels, enabling students with learning disabilities to participate meaningfully in learning activities while progressively developing greater self-regulation and academic independence (CAST, 2018; Zimmerman, 2000; Wang et al., 2025).

Role of Teachers as Mediators of AI-Supported Learning

The framework emphasizes the central role of teachers as instructional mediators who guide the integration of AI tools within classroom practice

(Vygotsky, 1978; Holmes et al., 2021). Rather than functioning as passive implementers of technology, teachers act as decision-makers who determine how, when, and to what extent AI-generated support is used to enhance learning outcomes (UNESCO, 2025; Kasneci et al., 2023). They interpret AI-generated feedback, contextualize it within curricular goals, and translate it into meaningful instructional actions that align with learners’ cognitive and emotional needs (Evmenova et al., 2024). In this sense, AI does not replace pedagogical expertise but rather extends it, enabling teachers to manage diverse learner profiles more effectively in inclusive classroom settings (Kasneci et al., 2023). Teachers also provide relational and emotional support that AI systems cannot replicate, including empathy, motivation, trust-building, and culturally responsive interaction, all of which are essential for students with learning disabilities who often require stable and supportive learning relationships (Ahmed et al., 2025).

Table 3: Teacher–AI–Student Interaction Roles

Actor	Role	Function in Framework	Key Responsibility
Teacher	Mediator	Interprets AI output, provides emotional support	Instructional decision-making
AI System	Scaffolder	Provides adaptive feedback and analytics	Real-time personalization
Student	Learner	Engages in SRL cycle with support	Developing self-regulation

In addition, teachers function as instructional designers within the AI-supported environment, ensuring that AI tools are aligned with learning objectives and pedagogical strategies (Holmes et al., 2021; Kasneci et al., 2023).

They evaluate the appropriateness of AI-generated recommendations, adjust task difficulty levels, and decide when human intervention is necessary to clarify misconceptions or provide deeper conceptual explanations (Kasneci et al., 2023). This supervisory role is critical in maintaining instructional quality and preventing the misuse or overdependence on automated systems (Holmes et al., 2021; Kasneci et al., 2023). Teachers also ensure that AI outputs are interpreted correctly by students, especially those who may struggle with abstract reasoning or self-directed learning processes, which are common challenges among learners with disabilities (Ahmed et al., 2025).

A key dimension of the teacher's role within this framework is the prevention of cognitive dependency on AI systems (Holmes et al., 2021). While AI tools provide continuous scaffolding, there is a risk that learners may become overly reliant on automated prompts, feedback, and solution generation, thereby limiting the development of independent self-regulation skills (Kasneci et al., 2023). To address this, teachers actively encourage students to engage in reflective dialogue about AI-generated feedback, prompting them to question, evaluate, and justify the suggestions provided by the system (Ahmed et al., 2025). This reflective practice helps students develop critical thinking skills and ensures that AI is used as a cognitive support tool rather than a replacement for thinking processes (Holmes et al., 2021).

Furthermore, teachers gradually facilitate the fading of scaffolding, which is a critical principle in supporting long-term self-regulated learning development (Vygotsky, 1978; Kasneci et al., 2023). As students demonstrate increased competence and confidence, teachers reduce the level of direct AI and instructional support, encouraging learners to assume greater responsibility for goal setting, monitoring, and reflection (Zimmerman, 2000; Penn & Ramnarain, 2025). This gradual release of responsibility helps transition students from externally supported learning toward autonomous self-regulation. In inclusive classrooms, this process must be carefully calibrated, as premature withdrawal of support may lead to frustration, while excessive support may inhibit independence (Kasneci et al., 2023; This integration ensures that inclusivity is embedded at both the design and implementation levels, enabling students with learning disabilities to participate meaningfully in learning activities while progressively developing greater self-regulation and academic independence (CAST, 2018; Zimmerman, 2000; Wang et al., 2025).

Teachers also play a crucial role in ensuring that AI integration remains ethically and pedagogically appropriate (Holmes et al., 2021; UNESCO, 2025). They monitor for potential biases in AI-generated recommendations, ensure equitable access to learning opportunities, and safeguard against unintended consequences such as reduced peer interaction or diminished critical engagement (Kasneci et al., 2023; This integration ensures that inclusivity is embedded at both the design and implementation levels, enabling students with learning disabilities to participate meaningfully in learning activities while

progressively developing greater self-regulation and academic independence (CAST, 2018; Zimmerman, 2000; Wang et al., 2025). By maintaining oversight of AI use, teachers help preserve the human-centred nature of education while leveraging the efficiency and adaptability of technology (Evmenova et al., 2024).

Overall, the teacher's mediating role ensures that AI-supported learning remains balanced, intentional, and aligned with inclusive education principles (CAST, 2018; Layachi & Pitchford, 2025). The combination of human judgment and artificial intelligence creates a hybrid instructional system in which teachers retain pedagogical authority while AI enhances their capacity to support diverse learners effectively (Kasneci et al., 2023).

Learner-Centred Design for Students with Learning Disabilities

At the centre of the proposed framework are students with learning disabilities, whose cognitive, motivational, and metacognitive characteristics fundamentally shape the design and implementation of the entire system (Ahmed et al., 2025). The framework recognises that these learners are not a homogeneous group; rather, they present diverse profiles of strengths and difficulties that influence how they engage with learning tasks (Fletcher et al., 2019; UNESCO, 2025; Layachi & Pitchford, 2025). Common challenges include limitations in executive functioning, difficulties in sustaining attention,

weaknesses in working memory, and reduced academic self-efficacy arising from repeated experiences of academic struggle ((Pagliara et al., 2024; Ahmed et al., 2025). These factors often interact in ways that hinder learners' ability to independently regulate their learning processes, particularly in complex or less structured educational environments (Zimmerman, 2000;). As a result, the framework positions AI-supported scaffolding as a structured and adaptive mechanism that compensates for these challenges while progressively building learner independence over time (Holmes et al., 2021; Kasneci et al., 2023).

Within this context, AI-supported scaffolds are intentionally designed to provide high levels of structure during initial learning phases, particularly in goal setting, task planning, and strategy selection (Ahmed et al., 2025). However, unlike rigid instructional systems, these supports are adaptive and responsive, meaning they adjust in intensity based on learner performance and developmental progress (Pagliara et al., 2024). This ensures that learners are not permanently dependent on external assistance but are instead gradually guided toward internalisation of self-regulatory processes (Zimmerman, 2000). The framework therefore adopts a developmental perspective in which support is systematically reduced as competence increases, allowing learners to transition from externally regulated learning to more autonomous self-regulation (Vygotsky, 1978; Zimmerman, 2000).

Table 4: Expected Learning Outcomes for Students with Learning Disabilities

SRL Component	Development Area	AI Contribution	Expected Improvement
Goal Setting	Planning skills	Guided decomposition of tasks	Increased task initiation
Self-Monitoring	Attention regulation	Real-time progress tracking	Improved focus and persistence
Metacognition	Awareness of thinking	Reflective prompts	Better strategy awareness
Self-Efficacy	Confidence in learning	Positive feedback loops	Higher academic confidence

Through continuous and iterative interaction with AI systems across learning tasks, students are expected to develop a set of interrelated self-regulated learning competencies (Zimmerman, 2000; Irawan & Anwar, 2025). First, learners develop improved goal-setting abilities, as AI systems model and scaffold the process of breaking down complex academic tasks into achievable and structured objectives (Kasneci et al., 2023; Pagliara et al., 2024). Second, they develop enhanced self-monitoring skills, supported by real-time feedback mechanisms that make learning progress visible and actionable (Irawan & Anwar, 2025). Third, learners build stronger metacognitive awareness, as AI-generated prompts encourage reflection on strategies, decision-making processes, and task performance (Irawan & Anwar, 2025). Finally, students experience increased academic self-efficacy, as consistent feedback, structured support, and visible progress contribute to stronger beliefs in their own ability to succeed in academic tasks (Bandura, 1997; Ahmed et al., 2025).

Importantly, these outcomes do not occur in isolation but emerge through sustained interaction between learners, AI systems, teachers, and the broader instructional environment (Holmes et al., 2021; Kasneci et al., 2023). The framework therefore conceptualises learning as an interactive and evolving process rather than a static intervention. This perspective aligns with research demonstrating that structured digital scaffolding, when integrated with self-regulated learning principles, can significantly enhance academic engagement, persistence, and strategy use among students with learning difficulties (Holmes et al., 2021; Melo-López et al., 2025). Ultimately, by placing students with learning disabilities at the centre of the framework, the model ensures that technological, pedagogical, and instructional decisions are driven by learner needs rather than system capabilities (CAST, 2018; UNESCO, 2025; Evmenova et al., 2024). This learner-centred orientation reinforces the goal of inclusive education, ensuring that all design elements contribute meaningfully to the

development of autonomy, competence, and long-term self-regulated learning capacity (CAST, 2018; Zimmerman, 2000; Pagliara et al., 2024).

In summary, the proposed framework integrates Self-Regulated Learning (SRL) theory, Artificial Intelligence (AI)-driven adaptive learning, and Universal Design for Learning (UDL) principles into a unified model for inclusive education (Zimmerman, 2000; Holmes et al., 2021; Kasneci et al., 2023). The framework conceptualizes learning as a dynamic and continuously evolving interaction among learners, teachers, and intelligent systems, rather than as a linear or isolated instructional process (Pagliara et al., 2024). Within this model, AI functions as an adaptive scaffolding mechanism that supports learners across the forethought, performance, and reflection phases of SRL by providing personalised guidance, real-time feedback, and data-driven insights that respond to individual learner needs and performance patterns (Kasneci et al., 2023). At the same time, UDL ensures that learning materials, activities, and assessments are designed to be inherently accessible, offering multiple means of representation, engagement, and expression to accommodate learner variability from the outset (CAST, 2018). This prevents exclusionary practices and ensures that students with diverse cognitive and learning profiles can meaningfully participate in the learning process (Melo-López et al., 2025).

In parallel, teachers remain central to the pedagogical ecosystem, functioning as instructional mediators who interpret AI-generated outputs, make informed instructional decisions, and provide essential relational, emotional, and contextual support that technology alone cannot replicate (Vygotsky, 1978; UNESCO, 2025; Kasneci et al., 2023). Their role ensures that AI integration is pedagogically grounded, ethically responsible, and responsive to the socio-emotional dimensions of learning (Holmes et al., 2021). Teachers also regulate the degree of AI support provided to learners, ensuring that scaffolding is appropriately calibrated and gradually reduced as learners demonstrate increasing competence in self-regulation (Zimmerman, 2000; Winne &

Hadwin, 1998; Kasneci et al., 2023). This balanced interplay between human expertise and machine intelligence establishes a hybrid instructional system that strengthens, rather than replaces, traditional pedagogical practices (Kasneci et al., 2023).

This integrated approach addresses a key gap in existing literature by moving beyond fragmented or isolated applications of technology, pedagogy, or learning theory. Instead, it proposes a cohesive and theoretically grounded system specifically designed to support the development of self-regulatory capacities among students with learning disabilities in inclusive classrooms (Kasneci et al., 2023). By aligning cognitive, motivational, and metacognitive processes with adaptive technological support and inclusive instructional design, the framework offers a comprehensive model for enhancing learner autonomy, academic engagement, and long-term educational success (Irawan & Anwar, 2025). Ultimately, it contributes to advancing inclusive education by ensuring that students with learning disabilities are not only supported in accessing learners within equitable and supportive learning environments (Melo-López et al., 2025).

3. Implications of the Proposed Framework

The proposed AI-supported Self-Regulated Learning (SRL) framework for students with learning disabilities in inclusive classrooms carries significant theoretical, practical, pedagogical, and policy implications. By integrating SRL theory, Artificial Intelligence (AI)-driven adaptive learning, and Universal Design for Learning (UDL), the framework advances current understandings of how technology can be meaningfully embedded within inclusive education to support learner autonomy and equity (Zimmerman, 2000; Ahmed et al., 2025).

From a theoretical perspective, the framework contributes to the expansion of SRL theory by situating self-regulation within an AI-augmented learning environment. Traditional SRL models emphasize learner-driven processes such as goal setting, self-monitoring, and self-reflection (Zimmerman, 2000). However, this framework extends these constructs by demonstrating how

AI systems can function as external cognitive regulators that scaffold each phase of the SRL cycle. This shift challenges the assumption that self-regulation must develop independently of technological support and instead positions AI as a mediating tool that facilitates the gradual internalisation of regulatory processes (Vygotsky, 1978; Zimmerman, 2000). In doing so, it contributes to emerging discussions in learning sciences that conceptualize cognition as distributed across human and technological systems (Irawan & Anwar, 2025).

Furthermore, the integration of UDL into the framework strengthens theoretical coherence by embedding accessibility as a foundational design principle rather than a supplementary accommodation. This aligns SRL development with inclusive pedagogical design, ensuring that variability in learner needs is anticipated rather than reacted to (CAST, 2018; Ahmed et al., 2025). The framework therefore advances a more holistic theoretical model in which cognitive, motivational, technological, and environmental factors interact dynamically to support learning (Irawan & Anwar, 2025).

From a pedagogical perspective, the framework has direct implications for classroom practice. Teachers are repositioned as instructional mediators who actively interpret AI-generated data and translate it into meaningful teaching actions (UNESCO, 2025; Melo-López et al., 2025). This role requires educators to develop new competencies in data literacy, AI interpretation, and adaptive instructional decision-making. At the same time, the framework reinforces the importance of human relational support, particularly for students with learning disabilities who benefit from emotional scaffolding, consistent feedback, and trust-based interactions. The teacher–AI partnership model ensures that technology enhances, rather than replaces, pedagogical expertise (Melo-López et al., 2025).

Utilizing AI-enhanced formative assessment strategies facilitates the utilization of real-time data analytics to guide instructional modifications, aiding educators in promptly

recognizing educational deficiencies, providing tailored interventions, and enhancing instructional differentiation (Achuthan, 2025). Additionally, the structured fading of AI scaffolds promotes the gradual development of learner independence, ensuring that students do not become overly reliant on technological assistance (Ahmed et al., 2025). This has important implications for designing classroom strategies that balance support with autonomy development.

From a special education perspective, the framework offers a structured pathway for addressing the persistent challenges faced by students with learning disabilities, including difficulties in executive functioning, attention regulation, and academic self-efficacy (Wang et al., 2025). By embedding adaptive scaffolding within each phase of the SRL cycle, the framework provides continuous and personalised support that aligns with individual learning profiles. This contributes to more equitable learning experiences by ensuring that students with diverse cognitive needs receive timely, targeted, and accessible interventions (Evmenova et al., 2024).

At the policy level, the framework highlights the need for systemic investment in AI infrastructure, teacher professional development, and inclusive digital education strategies. Educational policymakers must recognise that effective AI integration requires more than technological access; it requires sustained training for educators, ethical guidelines for data use, and equitable distribution of digital resources (Evmenova et al., 2024). Without such support, there is a risk that AI-enhanced learning systems may widen existing educational inequalities rather than reduce them (UNESCO, 2025).

Moreover, the framework underscores the importance of ethical considerations in AI deployment, particularly regarding data privacy, algorithmic bias, and learner dependency (Kasneci et al., 2023; Holmes et al., 2021). Policymakers and educational institutions must ensure transparent data governance structures and implement safeguards that protect vulnerable

learners, including students with learning disabilities, from potential misuse of educational data or biased algorithmic decision-making (Evmenova et al., 2024).

Finally, the framework has implications for future instructional design and curriculum development. It encourages educators and instructional designers to move beyond static content delivery toward adaptive, learner-centred ecosystems that integrate AI tools, metacognitive scaffolds, and inclusive design principles (Evmenova et al., 2024). This shift supports the development of future-ready learners who are not only academically competent but also capable of self-regulating their learning in increasingly digital and automated educational environments (Wang et al., 2025).

In summary, the proposed framework offers a comprehensive model that bridges theory and practice by demonstrating how AI, SRL, and UDL can be integrated to enhance inclusive education. Its implications extend across classroom practice, teacher development, policy design, and special education, ultimately contributing to more equitable, adaptive, and learner-centred educational systems (CAST, 2018; Holmes et al., 2021; Kasneci et al., 2023).

4. Conclusion

This study developed an integrated conceptual framework that combines Self-Regulated Learning (SRL), Artificial Intelligence (AI)-driven adaptive learning, and Universal Design for Learning (UDL) to support students with learning disabilities in inclusive classrooms. The framework responds to a critical gap in the existing literature, where SRL processes, inclusive pedagogical design, and AI technologies are often examined in isolation rather than as interconnected components of a unified learning system. By positioning learning as a dynamic interaction between learners, teachers, and intelligent systems, the framework provides a more holistic understanding of how self-regulatory competencies can be developed in digitally enhanced inclusive environments.

At its core, the framework is structured around Zimmerman's SRL cycle, comprising the forethought, performance, and reflection phases (Zimmerman, 2000). Across these phases, AI functions as an adaptive scaffolding mechanism that supports goal setting, real-time monitoring, and reflective evaluation. This continuous support enables learners with learning disabilities to engage more effectively in learning processes that typically require high levels of executive functioning, metacognitive control, and sustained attention. In parallel, UDL principles ensure that learning content and activities are designed to be inherently accessible, offering multiple means of representation, engagement, and expression to accommodate learner variability (CAST, 2018).

A key contribution of this framework is the reconceptualization of AI not as a replacement for instruction, but as an augmentation tool that enhances teacher capacity and learner autonomy simultaneously. Teachers remain central as instructional mediators who interpret AI-generated insights, provide emotional and relational support, and regulate the gradual fading of scaffolds as learner competence develops. This teacher–AI partnership ensures that technological integration remains pedagogically grounded and ethically responsible, particularly in special education contexts where human

connection and contextual judgment are essential (Holmes et al., 2021).

The framework also highlights the importance of developing self-regulatory skills such as goal setting, self-monitoring, metacognitive awareness, and adaptive reflection through structured digital scaffolding. Over time, these supports are designed to shift responsibility from system-guided regulation to learner-driven self-regulation, thereby promoting academic independence and long-term learning resilience. This is particularly significant for students with learning disabilities, who often experience challenges in executive functioning and academic self-efficacy (Ahmed et al., 2025).

In conclusion, the proposed framework advances inclusive education by offering a comprehensive, theory-driven model that integrates cognitive, pedagogical, and technological dimensions of learning. It moves beyond fragmented approaches to provide a cohesive system for supporting diverse learners in developing self-regulated learning capabilities within AI-enhanced classrooms. Future research should focus on empirically validating this framework across different educational contexts, learner populations, and technological environments to further refine its effectiveness and scalability in real-world settings.

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6. Author Declaration

The author declares that this manuscript presents the conceptual framework has been developed through an extensive review of the literature in the areas of AI in education, self-regulated learning, and inclusive education for students with learning disabilities. This research does not involve any primary data collection, human participants, or animal subjects, and therefore does not require ethical approval or informed consent. The author confirms that this manuscript is original, has not been previously published or submitted for publication elsewhere, and has no conflicts of interest. The author accepts full responsibility for this manuscript and has submitted it to the International Journal of Special Education for publication.